Praise Worthy Prize
International Review of Automatic Control (I.RE.A.CO.), Vol. 10, N. 3
ISSN 1974-6059 May 2017

Prediction of the Number of Airport Passengers Using Fuzzy C-Means and Adaptive Neuro Fuzzy Inference System

Sunarsan Sitohang[1,2], Abba Suganda Girsang[2], Suharjito[2]

Abstract – *Airport requires a system to predict the number of passengers as a reference for airport development planning. In this study, the data used are time series of the number of passengers for eleven years. These data will form patterns which indicate the number of passengers each month in a year as the input data and the number of passengers next year as a target prediction. After the input data are clustered into three types using fuzzy C-means (FCM), the data are processed using adaptive neuro fuzzy inference system (ANFIS) to get the prediction data. The result shows that the "Mean Absolute Percentage Errors (MAPE) which represent the errors for 4 years are 4.20%, 5.70%, 5.36% and 4.47% with an average of 4.93% . Based on this result, FCM and ANFIS can be combined to predict the data time series.* ***Copyright © 2017 Praise Worthy Prize S.r.l. - All rights reserved.***

Keywords: *Prediction, Number of Passenger, FCM, ANFIS*

Nomenclature

CNC	Computer numeric control
SMO	An algorithm for solving the quadratic programming problems arising during the training of support vector machines; it is widely used for support vector machines
ANN	Adaptive neural network
OSSA	Optimized singular spectrum analysis
LLNF	Local linear neuro fuzzy
MAPE	Mean absolute percentage error
KNN	K-nearest neighbors
Fuzzy C-Means	
n	Number of sample data
m	Number of attribute data
Xij	Sample data
c	Number of cluster
w	Rank
$MaxIter$	Maximum iteration
ξ	Error smallest expected
U_0	Matrix Fuzzy
ANFIS	
y	Weighted average
w_1	1st rule
w_2	2nd rule
y_1	Weighted of 1st rule
y_2	Weighted of 2nd rule
$\overline{w}_1$	Weighted average of 1st rule
$\overline{w}_2$	Weighted average of 2nd rule
x_1	1st input of system
x_2	2nd input of system
A_1	1st parameter of activation function of 1st input system
B_1	1st parameter of activation function of 2nd input system
A_2	2nd parameter of activation function of 1st input system
B_2	2nd parameter of activation function 1st input of system
$c_{10}, c_{11}, c_{20}\, c_{12}, c_{21}, c_{22},$	Element of matrix
$\alpha_{A1}, \alpha_{B1}, \alpha_{A2}, \alpha_{B2}$	Degree of membership

I. Introduction

Transportation problems generally occur in nearly all major cities in the world. The problems include limited transport facilities, inadequate infrastructures, rapid urbanization, low level of discipline, and poor planning. These problems result in traffic congestion, delays, accidents, health problems and environmental problems that cannot be avoided anymore [1]. As key factors of the safety and sustainability of transportation system, individuals' insecure behaviors and statuses become hot issues and difficult problems in traffic safety engineering [2]. In relation to the transportation problems, prediction is needed as a reference for planning, such as research of Wijaya and Girsang [3]. The prediction of the number of passengers becomes important for preparing facilities in anticipation of rising passenger numbers, such as setting up additional flight schedules, lounge facilities, wider parking space and so forth. Wang et al. [4] simulated the passenger flow in a station hall during the spring festival by modifying the social force model; one of the methods used for prediction is Adaptive Neuro Fuzzy Inference System (ANFIS)[5][6]. Y.Zhang, J. Lei used ANFIS to predict the roughness of laser cutting effectively and

https://doi.org/10.15866/ireaco.v10i3.12003

improve quality level of laser cutting [7].

Ji et al. [8] proposed a cell-based model which includes two steps. The first step is to update speed, which is the cells the passenger can move in one time interval, and the other is to analyze the overtaking. ANFIS is a set of rules and an inference method combined in a structure connected then do the training and adaptation [5][6]. The goal of ANFIS is to find a model or mapping that will correctly associate the inputs (initial values) with the target (predicted values) [9]. PSO-ANFIS equalizer uses the training data and employs fuzzy C-means (FCM) clustering to model a wireless communication channel without knowledge of channel dynamics [10]. ANFIS to simulate solar radiation [11] Prediction using ANFIS which was implemented in various problems such as ANFIS and SMO models show an excellent performance for forecasting the hourly and daily power patterns using the temperature, wind direction, and time interval features for the wind speed [12], and forecasting to affect seat sales [13]. A study by Suharjito [14] used an optimized Neuro-fuzzy model with PSO to get the right model to improve the estimation effort at NASA dataset software project. Prediction models for thermal error compensation on CNC machine tools [15] predict the performance of a hybrid microgeneration system [16] and so forth. ANFIS is used for diagnosing dengue hemorrhagic fever [17]. Further, ANN is used for predicting stock price [18].

The provided data will be analysed using the forward chaining inference method to determine the kind of required nutrients [9]. M. Mirassid's research showed that ANFIS-FCM with a high accuracy was able to predict earthquake magnitude [19]. Based on that research, in this study, the FCM and ANFIS method are combined to predict the number of passengers. This study uses data from Hang Nadim Airport, Batam, Indonesia.

This prediction can be used as one of key variables for determining the addition of facilities and human resources in the airport. It can also be used as a consideration for increasing the number of flights.

II. Literature Review

Statistical modeling is a powerful tool for developing and testing theories by way of causal explanation, prediction, and description. Predictive model is any method that produces predictions, regardless of its underlying approach: Bayesian or frequentist, parametric or nonparametric, data mining algorithm or statistical model, etc.[20]. OSSA–LLNF the processed time series is modelled and forecasted via the LLNF model [21].

Prediction is like a puzzle, which is held by many people because they are curious about the future. Model prediction is very varied, such as income level of a city, the winner of a match, the election, weather, the power of an engine, a disease, and a lot of things that humans want to predict. The prediction methods can be classified into four broad categories: sequence based, clustering, template based and meta-predictor approaches [22]. A "training set" (seen data) is used to build the model i.e. determine its parameters during the so-called training session [23]. A "Validation set" (unseen data) is used to measure the performance of the network by maintaining its parameters constant. Term "unseen" refers to data that have never been used to update the weights of the network.[24].

II.1. Fuzzy C-Means (FCM)

Clustering is a process of grouping a set of physical objects or abstract objects into the same class [25]. The FCM program is applicable to various analysis problems. This program generates fuzzy partitions and prototypes for any set of numerical data [26]. There are two models of clustering: hierarchical clustering and non-hierarchical clustering.

FCM is a hierarchical method for creating the hierarchical composition of the object data which produces the clusters of nesting. Non-hierarchical clustering provides *n* number of objects and *k* which is the number of clusters formed and processing of such objects into groups based on specific optimization criteria, where each group is a representation of a cluster. The FCM algorithm has some steps as follows [27] [28] [6]:

1. Input data to be clustered X, in the form of a matrix $n \times m$ (n = number of samples data, m = attribute of each data), X_{ij} = Sampled data to – i (i = 1,2,3...,m).
2. Specify:
   a. The number of cluster = c;
   b. Rank = w;
   c. Maximum iterations = maxIter;
   d. Error smallest expected = ξ ;
   e. The objective function early = $P_0 = 0$;
   f. Early iterations = $t = 1$;
3. Generate a random number μ_{ik}, i – 1, 2, ..., n; k = 1, 2, ..., c; as elements of the partition matrix U:

$$U_0 = \begin{bmatrix} \mu_{11}(x_1) & \mu_{12}(x_2) & \cdots & \mu_{1c}(x_c) \\ \mu_{21}(x_1) & \mu_{22}(x_2) & \cdots & \mu_{2n}(x_n) \\ \vdots & \vdots & & \vdots \\ \mu_{c1}(x_1) & \mu_{c2}(x_2) & & \mu_{cn}(x_n) \end{bmatrix} \quad (1)$$

The matrix of fuzzy clustering partition must meet the following conditions:

$$\mu_{ij} = [0,1], 1 \le i \le n; 1 \le k \le c \quad (2)$$

$$\sum_{i=1}^{n} \mu_{ik} = 1; 1 \le k \le c \quad (3)$$

$$0 < \sum_{k=1}^{c} \mu_{ik} < c, 1 \le i \le n \quad (4)$$

4. Calculate the center of cluster to - k ; v_{kj}, with k=1, 2, ..., c; and j=1, 2, ..., m:

$$v_{ij} = \frac{\sum_{k=1}^{n}(\mu_{ik}) \cdot x_{kj}}{\sum_{k=1}^{n}(\mu_{ik})^{w}} \pi r^2 \tag{5}$$

5. Fix the degree of membership of each data on each cluster (fixed matrix partitioning):

$$v_{ij} = \left[\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{2/(w-1)}\right]^{-1} \tag{6}$$

with:

$$v_{ij} = d(x_k - v_i)\left[\sum_{j=1}^{c}\left(x_{kj} - v_{ij}\right)\right]^{1/2} \tag{7}$$

6. Calculate the objective function at iteration - t, Pt:

$$J(U, V; X) = \sum_{k=1}^{n}\sum_{j=1}^{c}(\mu_{ik})^{w}(d_{ik})^{2} \tag{8}$$

7. Check the condition stops

If : (| Pt-Pt-1 | < ξ) or (t > maxIter)
then stop; (9)
If not : t=t +1, repeat step 4

$$X = \frac{x_1 + x_2 + x_1 \dots \dots + x_n}{n} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{10}$$

where X = mean, n = a lot of data, x_i = data value to i:

$$\left(\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{\frac{1}{2}} \tag{11}$$

where n = The number data, x_i = the data value to - i, x_i = the avarage value of the data.

II.2. Adaptive Neural Fuzzy Inference System (ANFIS)

Fuzzy model can be used instead of perceptron with many layers.

In this case, the system can be divided into two groups: one group of similar neural network with weights of fuzzy and activation function fuzzy, and other groups such as neural network with input in fuzzy right on the first or the second layer, but the weights on the neural network are not in fuzzy right. Neuro fuzzy is the second group.

Suppose there are two inputs x_1, x_2, and one output. There are two rules based on Sugeno models [29]:

If x_1 *is* A_1 *and* x_2 *is* B_1 *then* $y_1 = c_{11}x_1 + c_{12}x_2 + c_{10}$
If x_1 *is* A_2 *and* x_2 *is* B_2 *then* $y_2 = c_{21}x_1 + c_{22}x_2 + c_{20}$

If α predicates for the second rules are w_1 and w_2, then a weighted average can be calculated:

$$y = \frac{w_1 y_1 + w_2 y_2}{w_1 + w_2} = \bar{w}_1 y_1 + \bar{w}_2 y_2 \tag{12}$$

ANFIS network consists of some layers as shown in Fig. 1 [30].

The output of each neuron in the form is provided by the membership degree of input membership functions, namely $\alpha_{A1}(x_1)$,$\alpha_{B1}(x_2)$, $\alpha_{A2}(x_1)$ or $\alpha_{B2}(x_2)$:

$$\mu(x) = \frac{1}{1 + \left|\frac{x - c}{a}\right|^{2b}} \tag{13}$$

{a,b,c} are the parameters, b = 1.

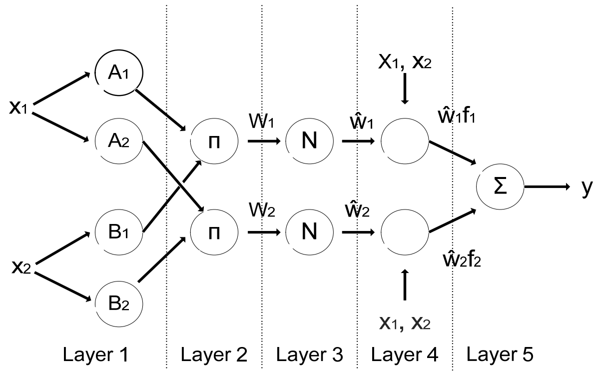

Fig. 1. ANFIS Network Architecture [30]

a. Each neuron in the second layer of neurons remains, so that the output is the result of input. Typically used the AND operator. Each node represents a predicate of the rule to the α - i.
b. Each neuron in the third layer is in the form of fixed node that is the result of the calculation of the ratio of α predicate (w), of the rules to - i to the total number of α predicate.

$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, \text{with i } = 1{,}2 \tag{14}$$

c. Each neuron in the fourth layer is adaptive to an output node:

$$\bar{w}_i y_i = \bar{w}_i(c_{i1}x_1 + c_{i2}x_2 c_{i0}) \tag{15}$$

d. Each neuron in the fifth layer is a fixed node which is the sum of all inputs.

III. Proposed Method

The framework of this study is presented in several steps, as shown in Figure 2.

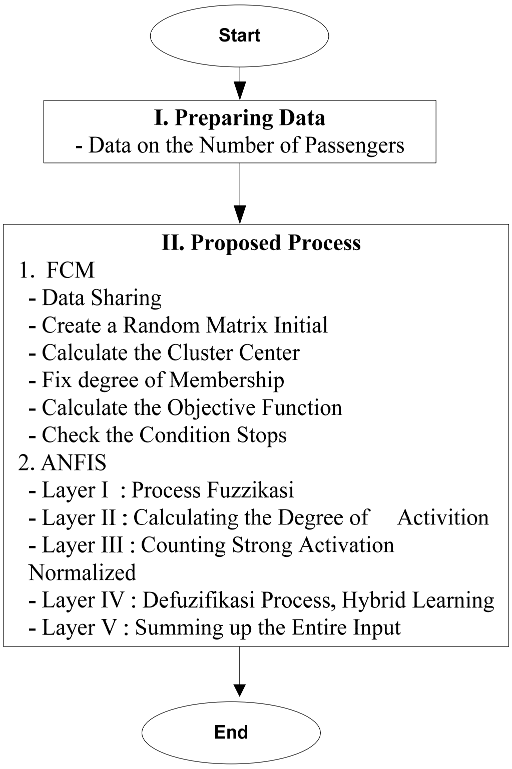

Fig. 2. Framework research methodology

Step I (Preparing Data)

The data include monthly data from 2004 to 2014.

Based on the data, pattern will be established based on the following principles:

Time series data on the number of passengers Hang Nadim Airport Batam are $x_1, x_2, x_3, \ldots\ldots, x_n$. The problem is how to predict the number of passengers x_{n+1} based on $x_1, x_2, x_3, \ldots\ldots, x_n$. The structure of the data pattern can be formed as follows:

[X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12} (2004) target X_1 (2005)]

[X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12} (2004), X_1(2005) target X_2(2005)]

[X_{12} (2013), X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11} (2014) target X_{12} (2014)]

Step II (Proposed Process)

There are two important processes in the steps:

1. Fuzzy C-Means (FCM)

At this step, the number of passengers will be classified according to the FCM algorithm.

Furthermore, the data will be categorized into three clusters based on high, medium and low number of passengers.

At first, the center of the cluster's initial condition is still not accurate. Each data point has a degree of membership for each cluster.

However, after many iterations, the center of the cluster will be able to move towards the right location. This loop is based on minimization of the objective function that describes the distance from data supplied to center cluster membership degree weighted by the data points.

2. Adaptive Neuro Fuzzy Inference System (ANFIS)

Once the data are clustered by FCM, the mean and standard deviation for each cluster are calculated using the Eqs. (10) and (11), respectively. The function membership is calculated based on the mean (variable a) and standard deviation (variable c) as shown by Eq. (13).

The degree of membership is normalized on the third layer as shown by Eq. (14). Eq.(15) shows the adaptive node to output which occurs on the fourth layer.

Adaptive node is contained in the first and fourth layers. The knot on the first layer contains a parameter premise that is non-linear, while the fourth layer contains linear consequent parameters. To update those parameters as a learning in neural network, ANFIS uses two combination methods, namely the 'forward pass' and 'backward pass'.

The next step ANFIS is fuzzification, calculating the degree of activation, hybrid learning, and aggregating all input. Last, the result of MAPE is calculated.

IV. Analysis and Discussion

The data are taken from the the number of passengers at Hang Nadim Airport in 11 years from 2004 through 2014 as shown in Table I.

TABLE I
TIME SERIES DATA 2004 TO 2014

Month	Years										
	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
January	85133	94457	104323	108549	113798	112594	117038	128025	146719	166100	179816
February	70370	81633	82278	84286	100815	98912	116430	120208	126662	142605	166112
March	70261	80137	85666	104824	119197	119481	118200	129077	141621	162974	163616
Appril	70730	74168	94189	96713	102516	109041	131221	124445	135957	151576	156891
May	81468	74862	94924	107127	104028	115868	141258	129927	145603	171595	179258
June	79590	77602	98819	113817	101060	116094	130170	133792	151331	179851	194037
July	88388	91995	111541	129410	103589	124985	139910	145414	157635	170306	199632
August	82934	80147	105651	121654	106084	115313	123651	130132	175574	188548	192180
September	80180	83900	106459	108145	98206	121269	135045	133259	147820	155232	169505
October	74468	82924	116690	127759	97566	115176	137733	145835	168182	177047	188957
November	84891	81362	102137	106361	104030	122099	138279	143574	165351	171332	177164
December	88736	97406	125085	124288	116894	128962	138415	143773	171754	187124	200888

TABLE II
THE PATTERN DATA

Data	Data Input												Target
Patterns	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	
1	85133	70370	70261	70730	81468	79590	88388	82934	80180	74468	84891	88736	94457
2	70370	70261	70730	81468	79590	88388	82934	80180	74468	84891	88736	94457	81633
3	70261	70730	81468	79590	88388	82934	80180	74468	84891	88736	94457	81633	80137
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
118	177047	171332	187124	179816	166112	163616	156891	179258	194037	199632	192180	169505	188957
119	171332	187124	179816	166112	163616	156891	179258	194037	199632	192180	169505	188957	177164
120	187124	179816	166112	163616	156891	179258	194037	199632	192180	169505	188957	177164	200888

Suppose the number of passengers in each year is $x_1, x_2, x_3, \dots\dots, x_n$. The problem is predicting how many passengers at x_{n+1} based on $x_1, x_2, x_3, \dots\dots, x_n$. The structure of the data pattern is formed as follows .

[X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12} (2004) target X_1 (2005)]

[X_2, X_3, X_4, X_5, X_6,X_7, X_8, X_9, X_{10}, X_{11},X_{12} (2004), X_1(2005) target X_2(2005)]

[X_{12} (2013), X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11} (2014) target X_{12} (2014)].

Thus, the data pattern 120 will be formed as shown in Table II or Figure 3. It shows that the input data are in blue line and the target data are in red line. This pattern data consists of two parts: training and test data.

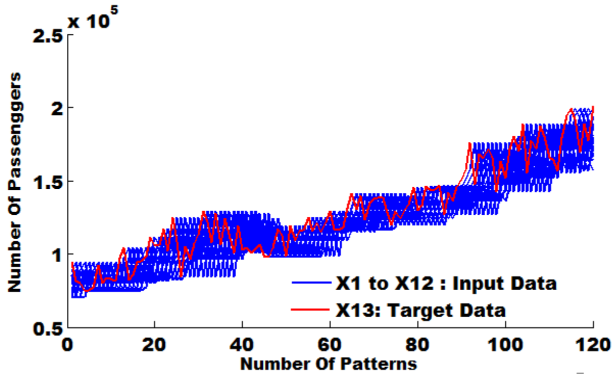

Fig. 3. Data Patterns for 2004-2014

Therefore, the pattern data can be split into two parts as presented in Figures 4 and 5.

Figure 4 represents the training data which are the 1st to 72th of data pattern of Figure 3, while Figure 5 represents the test data which are 73th to 120th data pattern of Figure 3.

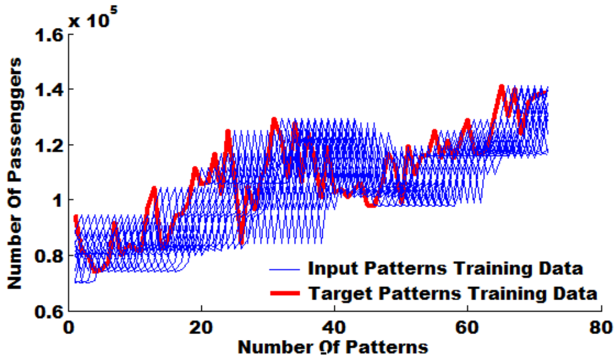

Fig. 4. Pattern Training Data

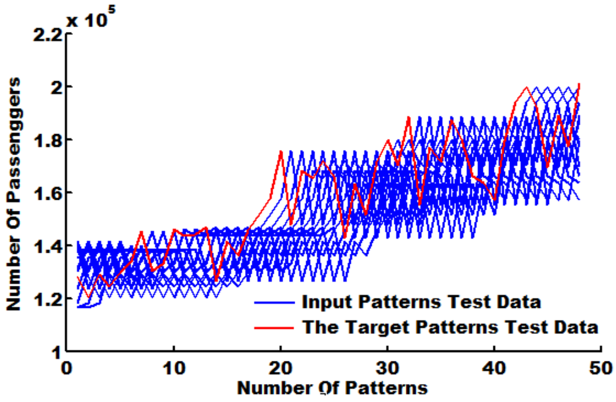

Fig. 5. Pattern Data Test

The pattern training data are clustered using FCM with number of clusters (C=3), rank (W=2), MaxIter=100), the smallest error to be expected (ξ = 0,0001).

The result FCM is shown in Figure 6 below.

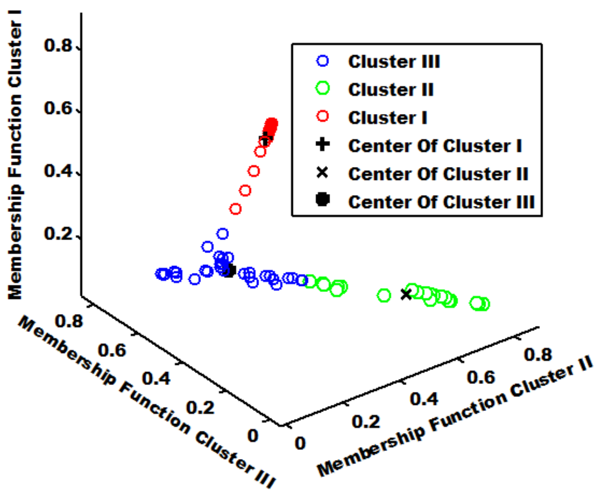

Fig. 6. Clustering training using FCM

The training data (72 data) are clustered into 3 groups which have the center clusters by using FCM as shown in Figure 5. The mean and standard deviation for each cluster obtained are shown in Tables III and IV. After the process of training data patterns, the learning process is conducted by forming a ANFIS architecture and FIS rules as shown in Figure 6 and Figure 7. Figure 8 shows the actual data (red line) and the prediction data (blue line), while the rate error is shown in Figure 9.

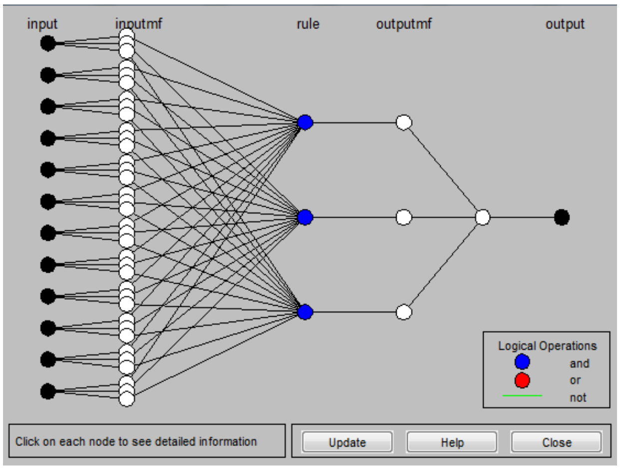

Fig. 7. Architecture ANFIS

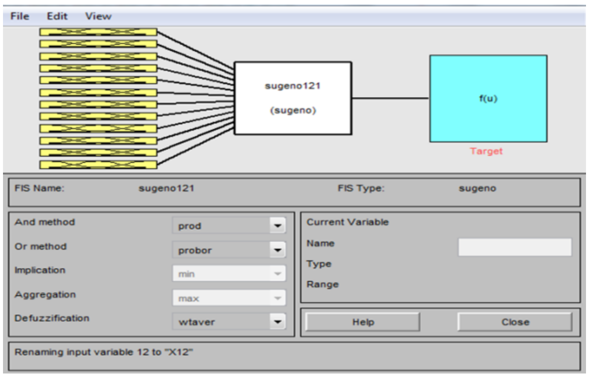

Fig. 8. Architecture FIS

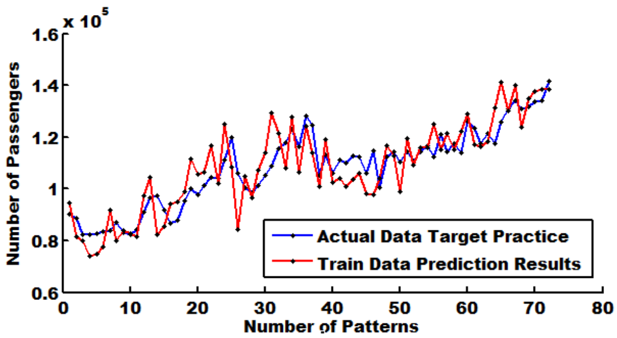

Fig. 9. The Data Actual and Prediction

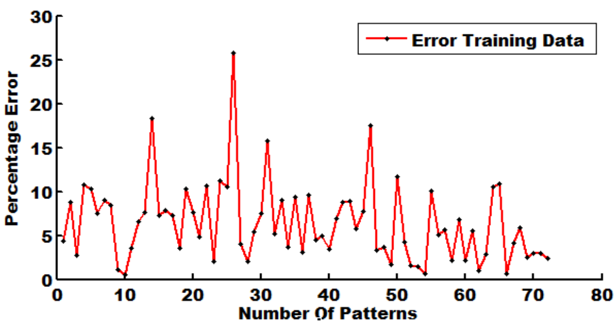

Fig. 10. Percentage Error of Training Data

Based on the chart in Figure 9, the trained data are formed by FIS; there is only one pattern training data error which exceeds beyond 20 %. Once the result is obtained, the data test is conducted using FIS. The result is shown in Figure 10 and Figure 11. The red line in Figure 10 represents the target data pattern, and the blue line represents the prediction.

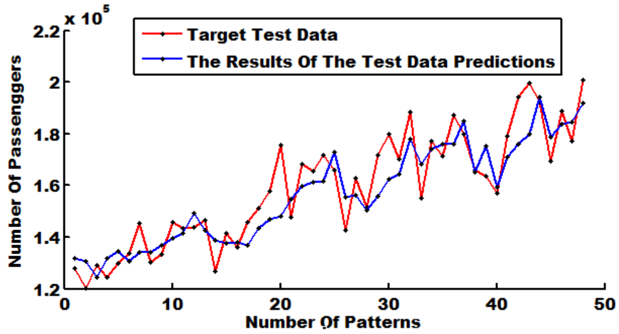

Fig. 11. The Target Data Test and Prediction

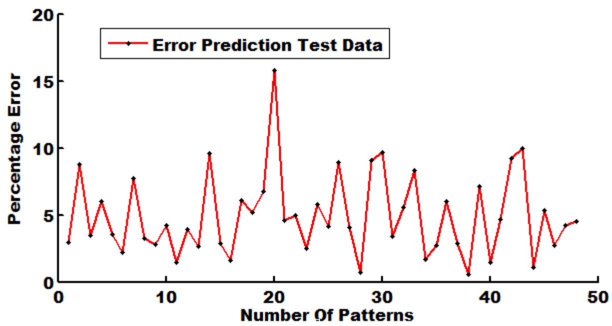

Fig. 12. Percentage Error of Testing Data

Based on Figure 12, the error more than 10% occurs only once in the 20th pattern with 15.76 %. The average MAPE of 72 data (72 data) is 4.93 %.

Combining ANFIS and FCM, there is a significant error reduction with other methods, around 1 to 2 % or using ANFIS only. If there are many input variables, then ANFIS will not be able to execute the rule formed. For example, in this study, there are 12 variables, which are X1-X12; then, the rule formed 12 12, very much. With the FCM, then the rule will be clustered into 3 parts. As a suggestion, the merging of these two methods should not be used to predict data that show very drastic ups and downs. In further research, ANFIS can be combined with other methods such as PSO, KNN, and Naive Bayes. In order to create the training data, the validity and reliability of data should be tested first. So, the prediction engine in the form of ANFIS will be more accurate.

V. Conclusion

This paper proposes the combination of Fuzzy Cluster Mean (FCM) and Adaptive Neuro Fuzzy Inference System (ANFIS) to predict the number of passengers at Hang Nadim Airport, Batam, Indonesia. The results show that the performance is relatively good. It is shown by the average MAPE 4.93 %.

This research can be extended by combining the other algorithms to enhance weight of variable in ANFIS, such as particle swarm optimization, genetic algorithm, and so forth.

References

[1] T. Litman and D. Burwell, "Issues in sustainable transportation," *Int. J. Glob. Environ. Issues*, vol. 6, no. 4, pp. 331–347, 2006.

[2] Z. Xie, L. Jia, Y. Qin, and L. Wang, "A hybrid temporal-spatio forecasting approach for passenger flow status in chinese high-speed railway transport hub," *Discret. Dyn. Nat. Soc.*, vol. 2013, 2013.

[3] A. Wijaya and A. S. Girsang, "The Use of Data Mining for Prediction of Customer Loyalty," *CommIT J.*, vol. 10, no. 1, pp. 41–47, 2016.

[4] L. Wang, Q. Zhang, Y. Cai, J. Zhang, and Q. Ma, "Simulation study of pedestrian flow in a station hall during the Spring Festival travel rush," *Phys. A Stat. Mech. its Appl.*, vol. 392, no. 10, pp. 2470–2478, 2013.

[5] Santoso, I., Gulo, R., Girsang, A., An Adaptive Cat Swarm Optimization Based on Particle Swarm Optimization Approach (ACPSO) for Clustering, (2016) *International Review on Computers and Software (IRECOS)*, 11 (1), pp. 20-26.

[6] Indrawati, A., Girsang, A., Electricity Demand Forecasting Using Adaptive Neuro-Fuzzy Inference System and Particle Swarm Optimization, (2016) *International Review of Automatic Control (IREACO)*, 9 (6), pp. 397-404.

[7] Y. Zhang and J. Lei, "Prediction of Laser Cutting Roughness in Intelligent Manufacturing Mode Based on ANFIS," *Procedia Eng.*, vol. 174, pp. 82–89, 2017.

[8] X. Ji, X. Zhou, and B. Ran, "A cell-based study on pedestrian acceleration and overtaking in a transfer station corridor," *Phys. A Stat. Mech. its Appl.*, vol. 392, no. 8, pp. 1828–1839, 2013.

[9] N. Sevani and Yosua Jaya Chandra, "Web Based Application for Early Detection of Vitamin and Mineral Deficiency," CommIT (Communication & Information Technology) Journal 10(2), 53–58, 2016.

[10] G. Model, "Article in press," 2016.

[11] Lanre Olatomiwa, Saad Mekhilef, Shahaboddin Shamshirband, Dalibor Petković, Adaptive neuro-fuzzy approach for solar radiation prediction in Nigeria, *Renewable and Sustainable Energy Reviews*, Volume 51, 2015, Pages 1784-1791.

[12] H. G. Lee, M. Piao, and Y. H. Shin, "Wnd power pattern forecasting based on projected clustering and classification methods," *ETRI J.*, vol. 37, no. 2, pp. 283–294, 2015.

[13] M. Varedi, "Forecasting seat sales in passenger airlines: introducing the round-trip model," *Management*, 2010.

[14] Suharjito, S. Nanda, and B. Soewito, "Modeling software effort estimation using hybrid PSO-ANFIS," in *Proceeding - 2016 International Seminar on Intelligent Technology and Its Application, ISITIA 2016: Recent Trends in Intelligent Computational Technologies for Sustainable Energy*, 2017.

[15] A. M. Abdulshahed, A. P. Longstaff, and S. Fletcher, "The application of ANFIS prediction models for thermal error compensation on CNC machine tools," *Appl. Soft Comput. J.*, vol. 27, pp. 158–168, 2015.

[16] L. Yang and E. Entchev, "Performance prediction of a hybrid microgeneration system using adaptive neuro-fuzzy inference system (ANFIS) technique," *Appl. Energy*, vol. 134, pp. 197–203, 2014.

[17] M. Legowo, N., Kanigoro, B., Salman, A. G., & Syafii, "Adaptive Neuro Fuzzy Inference System for Diagnosing Dengue Hemorrhagic Fever," in *Asian Conference on Intelligent Information and Database Systems*, 2015, pp. 440–447.

[18] Y. B. Napitupulu, T. A., & Wijaya, "Prediction Of Stock Price Using Artificial Neural Network: A Case Of Indonesia.," *J. Theor. Appl. Inf. Technol.*, vol. 54, no. 1, 2013.

[19] M. Mirrashid, "Earthquake magnitude prediction by adaptive neurofuzzy inference system (ANFIS) based on fuzzy C-means algorithm," *Nat. Hazards*, vol. 74, no. 3, pp. 1577–1593, 2014.

[20] G. Shmueli, "To explain or to predict?," *Stat. Sci.*, vol. 25, pp. 289–310, 2010.

[21] M. Abdollahzade, A. Miranian, H. Hassani, and H. Iranmanesh, "A new hybrid enhanced local linear neuro-fuzzy model based on the optimized singular spectrum analysis and its application for nonlinear and chaotic time series forecasting," *Inf. Sci. (Ny).*, no. September, 2014.

[22] J. D. Atkins, S. Y. Boateng, T. Sorensen, and L. J. McGuffin, "Disorder prediction methods, their applicability to different protein targets and their usefulness for guiding experimental studies," *International Journal of Molecular Sciences*, vol. 16, no. 8. pp. 19040–19054, 2015.

[23] H. Hindarto and S. Sumarno, "Feature Extraction of Electroencephalography Signals Using Fast Fourier Transform," *CommIT (Communication Inf. Technol. J.*, vol. 10, no. 2, p. 49, 2016.

[24] M. O. F. Technology, "Anfis Based Data Rate Prediction for Cognitive Radio Anfis Based Data Rate Prediction," 2010.

[25] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*. 2012.

[26] J. C. Bezdek, R. Ehrlich, and W. Full, "FCM: The fuzzy c-means clustering algorithm," *Comput. Geosci.*, vol. 10, no. 2–3, pp. 191–203, 1984.

[27] H.-J. Zimmermann, *Fuzzy Set Theory—and Its Applications*. 2001.

[28] J. Yen and R. Langari, *Fuzzy Logic: Intelligence, Control, and Information*. 1999.

[29] S. Osowski, T. H. Linh, and K. Brudzewski, "Neuro-fuzzy TSK network for calibration of semiconductor sensor array for gas measurements," *IEEE Trans. Instrum. Meas.*, vol. 53, no. 3, pp. 630–637, 2004.

[30] J.-S. R. Jang, "Neuro-fuzzy and soft computing for speaker recognition," in *Proceedings of 6th International Fuzzy Systems Conference*, 1997, vol. 2, pp. 663–668.

Authors' information

[1]Department of Engineering , Putera Batam University, Kepulauan Riau, Indonesia.
E-mail: ssunarsan@gmail.com

[2]Computer Science Department, Binus Graduate Program, Bina Nusantara University, Jakarta, Indonesia.
E-mails: agirsang@binus.edu
suharjito@binus.edu

Sunarsan Sitohang obtained master in computer science in engineering informatics from the Departement of Engineering, Bina Nusantara University, Jakarta, Indonesia in 2016. He obtained a Bachelor of Computer Science from the Department of Engineering, Putera Batam University (UPB), Batam, Kepri, Indonesia in 2013. His research interest in artificial intelligence and fuzzy logic.

Abba Suganda Girsang is currently a lecturer at Master in Computer Science, Bina Nusantara University. He obtained his Ph.D. from the Institute of Computer and Communication Engineering, Department of Electrical Engineering, National Cheng Kung University, Tainan, Taiwan. He got his bachelor from the Department of Electrical Engineering, Gadjah Mada University (UGM), Yogyakarta, Indonesia, in 2000. He then pursued his masters degree in the Department of Computer Science in the same university in 2006–2008. He was a staff consultant programmer in Bethesda Hospital, Yogyakarta, in 2001 and also worked as a web developer in 2002–2003. He then joined the Department of Informatics Engineering in Janabadra University as a lecturer in 2003-2015. His research interests include swarm,intelligence,combinatorial optimization, and decision support system.

Suharjito is the Head of Magister in Information Technology Department of Binus Graduate Program in Bina Nusantara University. He received under graduated degree in mathematics from The Faculty of Mathematics and Natural Science in Gadjah Mada University, Yogyakarta, Indonesia in 1994. He received master degree in information technology engineering from Sepuluh November Institute of Technology, Surabaya, Indonesia in 2000. He received the PhD degree in system engineering from the Bogor Agricultural University (IPB), Bogor, Indonesia in 2011. His research interests are intelligent system, Fuzzy system, image processing and software engineering